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Orchestrating Artificial Intelligence Capabilities for Healthcare Performance: Evidence from Digital Health Organisations in Bengaluru

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Abstract: his study develops and tests a capability-orchestration view of artificial intelligence (AI) enablement in digital healthcare organisations. It examines how strategy, core capability, proficiency and talent, organisational interest and implementation challenges relate to organisational performance.

Survey data were collected from 497 physicians, surgeons, healthcare administrators and information-technology managers across 36 AI-enabled healthcare organisations in Bengaluru, India. Each organisation contributed approximately 15–20 respondents. The 89-item questionnaire used five-point response scales. The source analysis combined descriptive statistics, correlations, chi-square tests, ANOVA, principal-components analysis and covariance-based structural equation modelling.

The workforce-productivity item set shows acceptable internal consistency (Cronbach's $\alpha = .852$) and sampling adequacy (KMO $= .819$; Bartlett $\chi^2 = 4,127.809$, $df = 300$, $p < .001$). Nine operational AI factors were extracted. In the reported structural model, organisational interest ($\beta = .249$), challenges facing AI enablement ($\beta = .248$) and proficiency/talent ($\beta = .234$) have the largest associations with overall performance, followed by core capability ($\beta = .106$) and AI strategy ($\beta = .103$). Overall performance is associated with leadership and decision making ($\beta = .215$), employee motivation ($\beta = .064$) and finance/investment capability ($\beta = .059$).

The paper moves beyond technology adoption to show AI enablement as an organisational capability portfolio. It also identifies a governance caution: challenge salience should not be interpreted as a beneficial causal effect without re-estimation and temporal evidence.

Keywords: Artificial intelligence, digital healthcare, organisational performance, dynamic capabilities, workforce productivity, structural equation modelling, India.

1. Introduction

Artificial intelligence in healthcare is often discussed as a collection of diagnostic algorithms, automated workflows and decision-support tools. Yet implementation outcomes depend on organisational conditions that sit around the technology: strategic intent, technical and managerial capability, specialist talent, workforce interest, governance and investment. This distinction matters because technically capable systems can fail to generate organisational value when workflows, roles and accountability remain unchanged. India's national AI strategy identifies healthcare as a priority sector for increasing access and affordability, while responsible-AI guidance stresses safety, transparency, privacy and accountability (NITI Aayog, 2018, 2021). The World Health Organization similarly argues that AI for health should protect autonomy, promote well-being and remain responsive and sustainable (WHO, 2021). These requirements make healthcare AI a socio-technical transformation rather than a simple information-technology installation. This paper asks: (1) which organisational capabilities are most strongly associated with performance in AI-enabled healthcare providers, and (2) how can those capabilities be organised into an actionable implementation architecture? Using data from 497 professionals in Bengaluru, it contributes employee-level evidence from an important but underrepresented digital-health ecosystem.

2. Theory and hypotheses

2.1. AI enablement as a dynamic organisational capability

Dynamic-capability theory explains how organisations sense opportunities, seize them through resource commitments and transform routines *(Teece, 2007)*. AI strategy provides direction; core capability enables integration; proficiency and talent supply specialised judgement; organisational interest creates mobilisation; and challenge management governs constraints. Together these resources support the complementary changes required for value realisation *(Vial, 2019)*.

H1a–e: AI enablement strategy, core AI capability, AI proficiency and talent, organisational interest in AI, and challenge-management capability are positively associated with overall organisational performance.

2.2. Performance as a workforce and resource outcome

Healthcare AI changes information processing and task allocation. Human–AI complementarity can strengthen decisions when professional judgement and machine capabilities are deliberately combined *(Jarrahi, 2018)*. Performance should therefore be reflected not only in operational or financial outcomes but also in leadership decision making, employee motivation and investment capacity.

H2a–c: Overall organisational performance is positively associated with leadership and decision making, employee motivation, and finance/investment capability.

3. Method

3.1. Setting, sample and instrument

The study used a cross-sectional survey of employees in 36 Bengaluru healthcare organisations that had operated AI initiatives for at least three years. The organisations were identified from healthcare directories; 15–20 respondents were randomly selected within each provider, yielding 497 usable responses. The sample comprised approximately 44% surgeons, 34% physicians, 11% healthcare administrators and 9% IT managers. A 30-person pre-test informed questionnaire refinement.

The instrument contained 89 statements across 13 domains: AI strategy; core capabilities; proficiency and talent; AI in management systems, clinical operations and diagnosis; provider interest; implementation challenges; leadership and decision making; employee motivation; training and development; finance/investment capability; and overall performance. Responses used five-point agreement, significance, challenge or satisfaction scales.

3.2. Analytical approach

The source study used descriptive and bivariate tests for preliminary objectives, principal-components analysis with varimax rotation for the 25-item workforce-productivity block, and maximum-likelihood SEM for the organisational-performance model. This paper prioritises the multivariate evidence. Because respondent-level data were unavailable for independent re-estimation, all coefficients and fit statistics are reported as archived results and causal language is avoided.

4. Results

4.1. Measurement exploration

The 25-item productivity block achieved $\alpha = .852$. KMO $=$ .819 and a significant Bartlett test ($\chi^2 = 4,127.809$, $df = 300$, $p < .001$) support factorability. PCA with varimax rotation converged after 11 iterations and retained nine components using a .50 loading threshold.

Table 1: Nine reconstructed operational factors from the rotated component solution.

Extracted capability	Operational meaning
AI competency	Diagnostic insight and complex-problem capability
AI alacrity	Faster interpretation, confidence and professional responsiveness
Defect-density reduction	Error detection and safer clinical processes
AI-enabled device	Digitally mediated access to information and action
Process streamlining	Workflow coordination and operational efficiency
AI vigilance	Alerts, surveillance and anticipatory clinical support
Patient-centric system	Personalised interaction and appointment access
Healthcare-practitioner assistance	Workload reduction and procedural support
Mechanised channel	Automated medication and imaging pathways

The largest reported antecedent coefficients belong to provider interest, challenge salience and proficiency/talent. Strategy and core capability remain statistically significant but smaller. On the outcome side, leadership and decision making show a more substantial relationship than motivation or finance/investment capability.

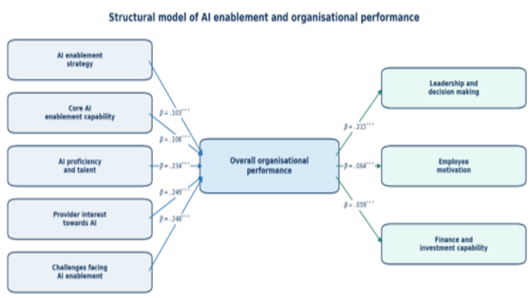

Figure 1: Reported structural-equation model. The challenges path represents challenge salience/governance intensity and should not be read as a beneficial causal effect.

Table 2: Structural relationships

Structural path	Reported estimate	p	Decision
AI strategy → performance	.103	$< .001$	Supported
Core AI capability → performance	.106	$< .001$	Supported
AI proficiency/talent → performance	.234	$< .001$	Supported
Provider interest → performance	.249	$< .001$	Supported
AI challenges → performance	.248	$< .001$	Supported*
Performance → leadership/decisions	.215	$< .001$	Supported
Performance → employee motivation	.064	$< .001$	Supported
Performance → finance/investment	.059	$< .001$	Supported

Table 3: Model-fit audit

Index	Reported value	Editorial assessment
χ^2	91.02	Exact-fit p is necessarily $< .001$ at $df = 21$; source criterion is inconsistent
χ^2/df	3.663	$91.02/21 = 4.334$, not 3.663
GFI / AGFI	.993 / .984	Reported as good
CFI / NFI / TLI	.975 / .985 / .971	Reported as good
RMSEA	.048	Reported as good, but inconsistent with the stated χ^2 and df

The incremental fit indices indicate strong fit, but the reported χ^2, degrees of freedom, χ^2/df and RMSEA are not mutually consistent. In addition, every path has the same critical ratio (15.748), which is improbable given different estimates and standard errors. A Q1 submission should therefore replace this table with output re-estimated from the raw covariance matrix and report standardised coefficients, confidence intervals, reliability, convergent/discriminant validity and common-method diagnostics.

5. Discussion

The results support a capability-orchestration account of healthcare AI. Organisational interest and talent carry larger reported associations than formal strategy or core capability, suggesting that value emerges when technical potential is mobilised by people and embedded in routines. Strategy remains necessary, but a strategy document alone is unlikely to change clinical work.

The positive coefficient for implementation challenges requires special care. A plausible interpretation is that organisations with deeper AI programmes both encounter more challenges and achieve greater performance, or that active governance makes challenges more visible. Cross-sectional data cannot distinguish these explanations. Treating the coefficient as evidence that challenges cause performance would be substantively misleading.

The nine operational factors show how AI may influence workforce productivity: diagnosis support, error reduction, workflow acceleration, vigilance, patient interaction and practitioner assistance. This is consistent with research that frames healthcare AI as augmentation rather than wholesale professional replacement (Davenport and Kalakota, 2019; Topol, 2019).

6. Implications

6.1. Managerial implications

Healthcare leaders should manage AI as a portfolio with five linked workstreams: strategic use-case selection; data and integration capability; clinical/technical talent; workforce mobilisation; and responsible-AI governance. Investments should be gated by clinical value, workflow fit, safety, privacy and measurable workforce outcomes. In India, health-data practices must be aligned with the Digital Personal Data Protection Act, 2023 and applicable rules, while clinical governance should retain human oversight.

6.2. Research implications

Future research should validate the nine-factor structure using confirmatory factor analysis, test measurement invariance across professional groups, and model organisation-level clustering. Longitudinal designs should separate adoption maturity from challenge exposure. Objective outcomes—turnaround time, diagnostic error, workload, patient experience and cost—should supplement self-reported performance.

7. Limitations

The cross-sectional, single-city design limits causal and geographic inference. Organisations were identified through directories, and the precise sampling frame of AI-enabled providers was unknown. Multiple respondents were nested within 36 organisations, but the archived analysis does not model clustering. All focal constructs are self-reported, increasing common-method risk. The PCA naming contains source inconsistencies, and the SEM fit and critical-ratio fields require re-estimation. These issues do not erase the study's substantive value, but they prevent the present version from being treated as a final confirmatory test.

8. Conclusion

Healthcare organisations realise value from AI through coordinated organisational capabilities, not algorithms alone. In this Bengaluru sample, talent, provider interest and challenge-management salience show the largest reported relationships with performance; leadership outcomes are more prominent than motivation or investment outcomes. The publication pathway is clear: retain the capability-orchestration contribution, recover the raw data, re-estimate the measurement and structural models, and report the corrected evidence transparently.

Submission note — Insert author identities, ethics approval and consent details, funding/conflict statements, CRediT roles and a journal-compliant data-availability statement.

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